Dual Networks of Knowledge Flows:
An Empirical Test of Complementarity in Software Ecosystems

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Abstract

We develop a conceptualization of the firm as simultaneously existing in multiple networks in which each network provides access to different knowledge resources and is subject to different governance mechanisms. At its most parsimonious, firms have two knowledge-acquisition mechanisms: a formal, fine-grained, contractual governance mechanism through inter-firm alliances and a non-formal, coarse-grained, non-contractual mechanism of spillover capture. We operationalize the conceptual model with data from the software industry, test the additive and super-additive effects of a firm's position in the alliance network and patent citation network, and interpret the results as evidence of dual knowledge flows.

Introduction

A firm's performance depends upon its internal capabilities and knowledge resources (Conner & Prahalad, 1996; Teece, Pisano, & Shuen, 1997) and its ability to access critical complementary resources from other firms within its ecosystem (Gulati & Gargiulo, 1999). Firms exploit their own, existing knowledge and explore others' knowledge to generate new knowledge (Cohen & Levinthal, 1990; March, 1991; Nonaka & Takeuchi, 1995) while sustaining their competitive advantage through their ability to reconfigure their knowledge base (Henderson & Cockburn, 1994; Kogut & Zander, 1992; Teece et al., 1997).

The patterns of interactions between firms and their knowledge resources can be described as a network (Powell, Koput, Smith-Doerr, & Owen-Smith, 1999; White, 2002). We can segment the different networks according to the governance mechanisms that they use (e.g., strategic alliances, non-contractual spillover, informal information trading, etc.). Transaction cost economics influences the resources firms seek from each network (Williamson, 1975): if a firm could get the *same* benefit from two different networks, it would choose the one that provides maximal benefits at the lowest cost. The resources available from each network are distinct yet complementary. As a result, we hypothesize that the different networks additively enhance firm performance and that there are interaction effects between networks that result in super-additive performance for well-positioned firms. We test these hypotheses in the Software Industry.

The Software Industry is a setting that calls for knowledge interdependence between firms to achieve product interoperability (Shapiro & Varian, 1999), where a network of relationships is key for a software firm's success (Campbell-Kelly, 2003). Knowledge interdependence arises, in part, because software products rely on the application programming interfaces (APIs) of other products. Thus, a software company must not only know about the APIs of other products, it must also know when those APIs will be released. Moreover, the APIs are not developed independently by each company. They are developed jointly through formal alliances and informal relationships. Relationship managers at the firms we spoke to describe a portfolio of relationships from strategic alliances to technology partnerships in which marketing strategies, product-line development, and API and integration approaches are negotiated. These relationships result in complementary sales, marketing, and software development activities.

In this study, we develop a conceptual model of a software firm's positions in two (dual) complementary networks governed by different mechanisms and exploiting different knowledge flows. Firms access and leverage fine-grained knowledge through formal, contractual mechanisms (henceforth referred to as the contractual network) (Gulati et al., 1999) such as alliances. In addition, firms access and leverage coarse-grained (Gulati et al., 1999) knowledge through non-formal, non-contractual mechanisms (henceforth referred to as the non-contractual network) such as informal-trading by employees (Saxenian, 1991), borrowing from others (March & Simon, 1958: 209), and capturing spillovers (Cohen et al., 1990). Some researchers have used patent-citations to measure knowledge flows (Trajtenberg, 1990). Importantly, the terms fine-grained and coarse-grained do not refer to the level of detail in the knowledge flow. Instead, the terms refer to qualitative differences: fine-grained knowledge is firm-specific and coarse-grained knowledge is more technology or industry specific.

Prior research studies on networks typically focus on one focal mechanism for resource access: Ahuja (2000a) focused on how alliance networks shape innovation; Podolny & Stuart (1995) focused on patent networks to develop concepts of interconnected niches within an industry; Morgan and Hunt (1999) focused on relationship marketing; Reddy and Czepiel (1999) focused on buyer-seller relationships; and Cohen and Levinthal (1990) focused on technology R&D activities. Such focused approaches to looking at knowledge flow conduits are valuable within specific functional domains (R&D, marketing etc.). However, there are compelling reasons to understand how these different mechanisms co-exist within organizations because of the inherent tradeoffs across these mechanisms as managers strive to benefit from structuring their network of relationships in ways to maximize value from complementary knowledge flows. In other words, we are interested in trying to understand how a firm's position in different networks of relationships creates value.

[Figure 1 goes about here]

A pair of networks can connect a focal firm to the same set of firms with different conduits represented by overlapping networks. Or, a focal firm can connect to a mix of same and different firms with different conduits represented by intersecting networks. Finally, a focal firm can connect to separate sets of firms represented by disjoint networks. From a statistical perspective, multiple networks could just be different ways of measuring the same thing (collinearity) or position in one network could predict the position of the firm in other networks (endogeneity). To the extent that these concerns are actualized, researchers and managers could focus on a single network. However, to the extent that these concerns are poorly placed, researchers and managers must focus on multiple networks.

Locating and accessing outside knowledge sources is not costless. When there are many sources of outside knowledge, the sources the firm selects are critical to what it learns and how it allocates its resources. Firms invest in joint ventures, research consortia, and R&D activities. They form alliances for distribution, marketing, and product development. Firms meet with customers, attend trade shows and analyze competitors. Both time and resources are limited; therefore, the firm must make allocation decisions that ultimately affect firm performance.

We hypothesize that pairs of networks are not identical, that different networks provide access to different resources, and that they are created through different tie formation mechanisms. These networks provide firms with different tradable resources (tangible and non-tangible) that lead to both the formation of the respective networks and a complementary effect on firms' performance (Brusoni, Prencipe, & Pavitt, 2001; Grant, 1996; Schrader, 1991). The networks may overlap to a greater or lesser extent, as diagrammed in Figure 1. The degree to which the dual networks contain the same firms is an empirical question, which we explore in the software industry and which is answered both statistically and in the visualizations in Appendix A. This paper confirms that the networks in which firms are embedded are distinct (almost disjoint) and that a firm's position in each network is additive and complementary to the firm's performance.

This paper is organized as follows. Section two develops the theory of complementary networks and hypotheses. Section three describes the empirical testing methodology, including the construction of the networks. Section four describes the research setting, dataset and variables. Section five describes the regression models and results. In section six we utilize network visualization techniques to provide additional insights into the phenomena. We discuss the results and directions for future research in section seven.

Theoretical Perspectives and Hypotheses

Two Mechanisms for Accessing Complementary Knowledge

Firms succeed by effectively accessing complementary knowledge resources from firms and other institutions in the broader ecosystem. In the biotechnology sector, Powell and his colleagues (Powell, Koput, & Smith-Doerr, 1996; Powell, White, Koput, & Owen-Smith, 2005) have shown that the linkages between a firm and its set of partners—formal alliances, technology licensing, links to universities etc.—are key conduits for obtaining external knowledge. An important finding from this stream of work is that there is no single linkage that governs effective knowledge flows across contexts and time, thus calling for a more comprehensive, holistic approach that recognizes multiple avenues of knowledge access.

In this vein, we focus on two mechanisms. One is inter-firm alliances and relationships that are governed by formal mechanisms of resource pooling and value appropriations (Gulati & Singh, 1998). These include license-sharing agreements, joint ventures, research consortia, joint R&D activities, and other activities governed by the formal agreements. Firms create interconnections for many reasons, such as access to financial capital, specialized knowledge, complementary assets, technical capabilities and new marketing channels (Oliver, 1990). For such reasons and others, firms form relationships with other firms and such moves create the network of relationships that act as the backdrop for competition and value delivery in this industry. We term this the *formal contractual mechanism*.

The other mechanism recognizes the non-formal interconnections that exist between companies. This may involve informal trading of know-how between employees in an industry (Saxenian, 1991; Schrader, 1991), relying on innovations by lead users (von Hippel, 1988), or involve borrowing best practices through participation in different business consortia and membership in industry associations (Rosenkopf, Metiu, & George, 2001a). Other practices of non-formal accessing and using knowledge from others are reverse engineering, product examination, and sharing of common customers. Each of these mechanisms has a different cost and level of effectiveness (which we don't pursue in this paper). Broadly, these mechanisms represent the capture of spillover (Cohen et al., 1990). Although spillover is sometimes directionless, the specific investments firms make to capture it give the resulting network directionality. We term this the *non-formal, non-contractual mechanism*.

We explore knowledge flow that results from this mechanism through the patent citation network. Firms make choices as to how to allocate their scarce attention. As a result of these choices, firms learn from specific other firms and frequently create new knowledge. In industries that utilize patents to protect intellectual property, new knowledge that results in novel innovation may be patented. As we discuss later in this paper, the US Patent and Trademark Office (USPTO) requires that the antecedents of the patented innovation are documented through patent citations. As a result, we are able to trace some of the direct and indirect knowledge flows that occur between firms due to their choices in the non-contractual network.

Key Characteristics of the Network Structure

Networks have become an important focus of attention in recent years in management research (Ahuja, 2000a; Baum, Shipilov, & Rowley, 2003; Burt, 1992; Freeman, Borgatti, & White, 1991; Granovetter, 1973; Powell et al., 1996; Uzzi, 1996). Researchers use a variety of constructs to conceptualize a firm's structural position in a network, the flows through the network, and the consequences to the firm of both structure and attendant flow. We rely on two constructs to capture network position: reach and embeddedness[4]. We make the simplifying assumption that knowledge flows,

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[4] Embeddedness is the extent to which the firms that the focal firm has ties to also have ties to each other. Reach is measured through closeness centrality and embeddedness is measured through the clustering coefficient. Actual variable definitions are provided in the section *Operationalization of Constructs*.

and that it flows through the network as a result of the specific investments firms make to access the knowledge of other firms.

Reach reflects the capacity of the knowledge flow from all other nodes to the focal firm under the assumption that the knowledge of a firm can be accessed directly (a single link exists between the focal firm and the other firm) and indirectly (focal firm A accesses the knowledge of firm C by accessing firm B, which accessed firm C directly). The flow quantity is a function of both the size of the conduits that connect the firms and the closeness (in graph theoretical terms) of the focal firm to the other firms in the network. Embeddedness reflects the degree to which a firm's alters[5] are linked to each other. Linked alters are assumed to share knowledge with each other and, as a result, posses overlapping knowledge with the focal firm.

Dual Networks of Knowledge Flows

We use two mechanisms (formal, contractual and non-formal, non-contractual) and two characteristics (reach and embeddedness) to develop a set of hypotheses on how firms position themselves to access knowledge resources in networks for effective performance. Our rationale is as follows: We hypothesize that the role of reach for both networks is to increase access to relevant and useful information, and critical complementary resources, from other firms. Within the contractual network we hypothesize that embeddedness aids in sense-making and acts as a constraint because the contractual network acts as both an information conduit and a coordination mechanism between firms. In contrast, non-contractual relationships are more about information flows and less about coordination; therefore, we limit our discussion within non-contractual relationships to the negative impact of redundant information due to embeddedness.

Reach in formal, contractual network. Firms access knowledge through their direct relationships as well as indirect relationships (Ahuja, 2000a). Better performing firms have ties to more diverse

[5] An alter is a node with a direct link to the focal firm.

knowledge sources and are better positioned to access key information and critical resources (Powell et al., 1996). We are beginning to see some consistent cumulative empirical findings that a firm's reach within a network of alliances contributes to innovation (Ahuja, 2000a; Powell et al., 1996) and to its subsequent sales and financial performance (Powell, Koput, Smith-Doerr, & Owen-Smith, 2001). While most of these findings have been based on studies in industries such as chemicals (Ahuja, 2000a), steel (Rowley, Behrens, & Krackhardt, 2000), financial services (Baum, Calabrese, & Silverman, 2000) and manufacturing (McEvily & Zaheer, 1999), the role of inter-firm alliances for knowledge access in the software industry has been less fully studied.

Since this industry is characterized by the need for inter-firm coordination for product launches due to interoperability requirements and uneven rates of change in the underlying technology architecture, alliances have been growing steadily in importance (Campbell-Kelly, 2003; Cusumano, 2004). Software applications are increasingly built by incorporating components developed by other companies and they are increasingly expected to work with (interoperate with) other software applications (not including the operating system).

The core argument is that such alliances increase the value of their joint products and services for end customers and/or lowers their joint costs of production depending on the business landscape in which firms cooperate and compete (Baum & Singh, 1994; Silverman & Baum, 2002). Reach is positive for firm performance because alliance partners facilitate the identification of opportunities, develop complementary products, provide access to complementary resources and competencies they don't otherwise possess, and coordinate product development and marketing activities.

Moreover, firms in the software industry do not fully exploit their own knowledge. They use alliances in order to leverage the knowledge they generate (Brusoni et al., 2001; Teece, 1998). For example, we spoke with a business intelligence firm with expertise in data mining that develops its own applications and helps other firms develop data mining capabilities for their products. Therefore, we expect that a firm's performance will be explained significantly by its strategic choices to enter into a set of formal relationships with firms in the extended industry network reflected by its reach.

H1: Reach in the formal, contractual network is positively associated with performance.

Embeddedness in formal, contractual network. As each firm pursues a strategy of alliance formation, the number of ties among a firm's alters increases, increasing embeddedness. Such embeddedness could play both enabling and constraining roles (see for example, White (2002)) as empirical research confirms both positive and negative consequences in different contexts (Coleman, 1988; Granovetter, 1985; Uzzi, 1997; Watts, 1999). Embeddedness facilitates trust and reduces the cost of monitoring network partners (Ahuja, 2000a; Coleman, 1988; Zaheer & Bell, 2005) while facilitating managerial sense-making and enhancing the collective firms' ability within the closed network to respond and adapt to fast-changing technological environments (Krackhardt & Stern, 1988; Rindfleisch & Moorman, 2001). Thus:

H2a: Embeddedness in the formal, contractual network is positively associated with performance.

A competing perspective is that firms become over embedded in local networks of other firms without connecting to the broader, fast-changing market. This is akin to March's (1991) argument against excessive exploitation without adequate exploration in organizational learning. If a focal firm's alters share information, then it may not receive as much unique information as the number of its alliance partners might suggest. The firm could get the same amount of unique information with fewer alliances, since the alliances provide redundant information. Moreover, it is unable to exercise a bridging position (Burt, 1992; Zaheer et al., 2005) and has less structural autonomy (Gnyawali & Madhavan, 2001), which reduces its status, power, and freedom of action.

Firms in dense clusters (parts of the network characterized by a high degree of transitive closure in which the partners of alliance partners are also in partnership) would seem to provide a bundle of products often purchased as a unit by customers. Since consumers depend upon the joint operation of the items in the bundle, vendors form alliances to manage the interdependencies between the individual products. Under such conditions, firms may be limited in their ability to independently set prices or expand their individual piece of the market. Thus, embeddedness is a form of social constraint (Gnyawali et al., 2001; Portes & Sensenbrenner, 1993), creating perhaps a paradox of embeddedness (Uzzi, 1997). Thus, a competing hypothesis is:

H2b: Embeddedness in the formal, contractual network is negatively associated with performance.

Reach in non-formal, non-contractual networks. Since von Hippel's (1988) finding on the role and prevalence of informal trading, there has been considerable interest in non-formal mechanisms for know-how exchange. Network researchers have recognized non-formal mechanisms through membership in common boards as imitative ways to understand practices (Galaskiewicz & Wasserman, 1989). Economic researchers have focused on how firms develop superior knowledge through internal R&D activities and learn from others through spillover effects (Cohen et al., 1990), where the value of spillover is due to the absorptive capacity created by internal R&D. Firms seek access to coarse-grained knowledge from spillovers through a variety of mechanisms—participation in conferences, tradeshows, and professional organizations; reading each other's publications; studying each other's patents, products, and related innovations; and hiring each other's employees. In some of these relationships the parties in the exchange are aware of each other (e.g., informal trading by engineers (Schrader, 1991)), in other relationships the parties may not be aware of each other (Cohen et al., 1990).

Reach in non-formal networks reflects breadth of direct and indirect knowledge sources accessed as organizations strive to balance exploration of new domains with the exploitation of current domains (March, 1991). In general, lower reach in non-formal networks reflects a conservative posture to limit knowledge to familiar domains while a higher level of reach signals a company's desire to seek, access and internalize knowledge from newer domains. Using patent-citations as an operationalization of non-formal access to knowledge, Rosenkopf and Nerkar (2001b) found that in their study of the optical disk industry, the impact of exploration on technological development beyond the optical disk domain was the greatest when exploration spanned organizational and technological boundaries, providing support for our hypothesis.

H3: Reach in the non-formal, non-contractual network is positively associated with performance.

Embeddedness in non-formal, non-contractual networks. When a focal firm gathers information from two other firms, A and B, that gather information from each other there is some inevitable overlap in the information the focal firm gathers from the two other firms. Some of the information that the focal firm gets from firm A is indirect knowledge from firm B, which the focal firm is also getting directly.

The overlapping information suggests that the firm is inefficient in its identification of knowledge sources. The firm could theoretically reduce the number of direct knowledge sources without reducing its actual knowledge flow. Embeddedness also reduces brokerage opportunities (Burt, 1992). If the firm has a unique set of knowledge sources, it can more easily recombine that knowledge to create innovative products. In an embedded collection of firms many firms have the same access to knowledge and, thus, the same recombinative opportunities. Therefore, we predict:

H4: Embeddedness in the non-formal, non-contractual network is negatively associated with performance.

Complementarity in Dual Networks: Additivity and Super-Additivity

Additivity arguments. What are the benefits to a firm for locating within multiple networks for access to critical knowledge resources? Following transaction cost economics (Williamson, 1975), we argue that to the extent a firm is located within multiple networks, these networks provide distinct benefits to the firm. If a firm could get the *same* benefit from two different networks, it would choose the one that provides maximal benefits at the lowest cost. Firms seek to develop a portfolio of relationships with different governance mechanisms such that the governance modes maximize value while minimizing transaction and coordination costs (Gulati et al., 1998). So, we expect firms to select their knowledge sources to maximize knowledge creation with optimal transaction and coordination costs.

The costs and benefits from the additive networks may vary for a number of reasons. The knowledge that flows from one firm to another may be technical, managerial, or market oriented, and industry differences influence the type and amount of knowledge that flows between firms. The mechanisms that firms use to protect valuable intellectual property (Levin, Klevorick, Nelson, & Winter, 1987) within different industries may also influence the type of information available in each network and the types of networks that exist within an industry. The selection of different network links may also be influenced by a firm's capacity to absorb the external knowledge due to the degree of difficulty associated with locating, accessing, and internalizing the requisite knowledge (Cohen et al., 1990).

Powell, White, Koput, & Owen-Smith (2005) argue that firms are multivocal: they gain access to different resources through relationships with distinct sets of firms that evolve over time. In this paper, we have sought to distinguish between contractual and non-contractual relationships that together provide access to valuable knowledge resources. Our belief is that these are mutually interdependent since relationships governed by one governance mechanism (e.g., contractual) do not provide access to resources that are governed by the other (e.g., non-contractual).

For example, Microsoft may participate in every major industry association to learn about different emerging technology trends (non-contractually) and form different sets of formal relationships to access complementary knowledge, which may be more immediately relevant for product enhancements. The firm may investigate new technologies based upon the innovator's customers' acceptance and independently decide to acquire the firm, license the technology, or complete with the innovator. The decision as to whether or not to forge a fine-grained, formal relationship with an innovator can be largely independent of the decision to form a non-contractual relationship with them. One mode of knowledge access is not a substitute for another. Firms need different antenna to search for different signals.

Thus, we assert that the formal alliance mechanisms do not provide a superior form of knowledge access to non-contractual mechanisms. Nor are non-contractual relationships substitutes for contractual relationships—they provide distinct and complementary access to knowledge resources, thus creating an image of a firm meshed in a complex and dynamic set of relationships. Based on the logic that formally contracted relationships confer access to distinctly different types of knowledge than non-formal, non-contractual relationships, we assert that these relationships are additive. Since the firm's reach in each network is hypothesized to be associated with its performance, and we assert that firms enter into multiple networks to gain access to complementary knowledge, we hypothesize that the firm's reach in multiple networks is additive to its performance. If this was not the case, the firm could increase its profitability by avoiding the cost of the additional network without a loss in performance. Thus:

H5: Reach in the contractual and non-contractual networks are additively associated with performance.

Super-additivity arguments. Next, we are interested in the question of whether the distinct resources are super-additive -- do they mutually reinforce one another? A set of resources are super-additive when returns to one type of resource are increased by having more of the other (Milgrom & Roberts, 1990). In other words: returns to both are greater than the returns to each in isolation. Since network linkages are important resources (Gulati et al., 1999), a potentially important research question is whether different types of relationships confer super-additive returns. Prior research focused on dyadic linkages have not examined this question, which lies at the core of understanding how firms navigate in multiple ecosystems spanning different constituencies and distinct types of organizational processes.

Our assertion is that a firm's reach and its subsequent access to knowledge in its contractual network increases the returns to the firm's reach in the non-contractual network, and vice versa. Organizations create new knowledge by applying their absorptive (Cohen et al., 1990) and combinative capabilities (Kogut et al., 1992) to externally sourced knowledge. Because firms enter into contractual relationships to gain access to this new knowledge, or are the targets of spillover search because they have this new knowledge, the generation of new knowledge makes the organization more attractive as a potential partner in both the contractual and non-contractual networks (Ahuja, 2000b; Podolny, 2001; Rosenkopf et al., 2001a). However, the type of knowledge created as a result of access to the fine-grained knowledge of the contractual network and the coarse-grained knowledge of the non-contractual network are different. In addition, the mechanisms by which a firm improves its reach in each network, and the mechanisms through which a firm's reach in one network increases its ability to position itself in the other network, are similar but not identical.

To continue with our earlier example of Microsoft and unnamed innovators – by attending industry conferences and exploring the new technologies of innovative companies, Microsoft can identify new partner opportunities. Its position in the non-contractual network can help it improve its position in the contractual network. By investing in access in the contractual network (partnerships), Microsoft is able to coordinate the release of products that had their genesis in the innovations of the non-contractual targets of Microsoft's investigations. In this case, Microsoft's position in the contractual network increases the returns to the knowledge gained in the non-contractual network.

The firm's reach in the contractual network is enhanced both by its previous position in that network (Gulati et al., 1999) and by its reach in the non-contractual (Ahuja, 2000b; Rosenkopf et al., 2001a). The firm's reach in the alliance network can be enhanced through its internal knowledge generation efforts, its knowledge generation efforts facilitated by fine-grained knowledge exchange, its knowledge generation efforts facilitated by spillover from the non-contractual network, and through endogenous improvement as the firm uses its existing network connections in both networks to learn about new partnership opportunities (Ahuja, 2000b; Gulati et al., 1999; Rosenkopf et al., 2001a).

A firm's moves in the alliance network are correlated with new product creation (Kotabe & Swan, 1995; Rothaermel, 2001; Rothaermel & Deeds, 2004) and new market entry, inducing the firm into examining new products and technologies and, thereby, improving its reach in the non-contractual network. By creating new venues for innovation, such new product and market entry generates demand for additional information from the non-contractual network, including information related to products, innovations, and market strategies. As the firm seeks additional spillover knowledge, it expands the list of firms from which it could potentially learn. Thus, the firm's reach in the non-contractual network is also the result of exogenous and endogenous tie formation as the firm develops ties based upon learning through the alliance network and its existing position within the non-contractual network.

In addition to the direct effect of position in one network improving the firm's ability to position itself in the other, network tie formation confers status to the well-positioned firm, which improves the firm's relative position in the network. Firms face uncertainty in selecting potential partners that are trustworthy, knowledgeable, or otherwise worth studying. Firms learn about each other's products by studying them, and they can learn about each other's customers and markets through conversations, industry events, and observation, but such data are incomplete. In order to reduce uncertainty, firms also utilize the position of potential alters in their respective networks as status indicators (Podolny, 2001). The status of a firm in one network increases its attractiveness to firms in the other network. Status in the contractual network makes a firm more likely to be viewed as a source of spillover, as well as a more attractive employer. New employees, in turn, can convey and help internalize spillover (Almeida & Kogut, 1999). Status in the non-contractual network – as a nexus of different technologies and markets – increases the firm's attractiveness to potential contractual partners.

We have previously characterized the additive returns to network position in terms of network reach and its associated access to knowledge. We now assert that the information available from the two networks has different characteristics (Haunschild & Beckman, 1998) and is also super-additive (Mowery, Oxley, & Silverman, 1996; Tanriverdi & Venkatraman, 2005). Information gathered from contractual relationships has the potential for being far more firm-specific or process oriented than the information gathered through spillover because contractual relationships allow for finer-grained information exchange. Contractual partners expend the effort and resources to gain access to resources that complement their own (Powell et al., 1996). Since network position is super-additive to both network formation and information access, and the information accessed in both networks is also super-additive, we formally hypothesize:

H6: Reach in the contractual and non-contractual networks are super-additively associated with performance.

Research Setting: The Software Industry

Software is an example of systems-based competition (Shapiro et al., 1999) in a knowledge-intensive industry that calls for high levels of interoperability (Baldwin & Clark, 1997) between suppliers of complementary products. Firms form alliances to develop new products, align product features, coordinate release cycles, and obtain more general knowledge regarding product features, software development processes, market information, customer data, and hidden algorithms. This is also a setting in which the importance of patents is growing: over 15% of all patents granted today are for software, which accounts for over 25% of the total growth in the number of patents between 1976 and 2001 (Bessen & Hunt, 2003). Thus, the patterns of contractual and non-contractual knowledge flow in a knowledge intensive industry, and the availability of data representing these flows, makes the software industry an ideal setting in which to test the theory of additivity and super-additivity.

We assembled a research database of firms in the prepackaged software industry (SIC code 7372) during 1995-1999 by combining data from multiple sources. We censored data prior to 1995 to avoid the uneven use of patents by software companies prior to that year, and we censored data after 1999 because many of the patents applied for in 1999 were not yet granted by the time our data was collected. Growth in the use of patents by software companies during our window was fairly even and monotonic. Space limitations prevent a detailed discussion, but an appendix is available on request.

To create our sample frame we started with the 899 firms with SIC code 7372 in the Compustat database. We then identified the top 50 firms (by sales) in each year from 1992 to 2002. The 105 unique firms so identified became our focal firms, of which 71 were granted at least one patent. We then eliminated from our sample firms that did not patent prior to the end of our sample window, firms that had no sales during our sample window, and observations (years) for which the remaining firms had no alliances. The resulting dataset consisted only of those firms that patent and form alliances, minimizing potential validity threats due to the endogeneity of the strategic decision to patent or form alliances (Shaver, 1998)[6]. After further restricting the dataset to firms for which we had at least three observations (including data for 1994 for lagged variables), the final dataset contained 56 firms and 238 firm/year observations.

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[6] Not all firms that acquire external knowledge subsequently patent. Thus, a patent count of zero does not imply zero learning. More likely, it implies a decision to not engage in patenting. Similarly, not all formal relationships are announced. Thus, zero alliances does not imply zero contractual relationships and zero fine-grained learning.

The 71 focal firms with patents cite 3,843 other non-focal firms (also included in our dataset). Our 71 focal firms applied for 3,891 patents during 1995-1999 that were subsequently granted. The non-focal firms applied for 314,026 patents during this same time period that were subsequently granted. We collected alliance data on the focal firms and their alliance partners from the SDC Corporation database. For every alliance and its participants (i.e., ultimate parent), we extracted the type and year of the alliance. Between 1995 and 1999, SDC recorded 92 alliances among the 71 focal firms and 2,679 alliances among the 71 focal and 853 non-focal alliance partners. We selected only those arrangements that involved significant knowledge transfer. Of the 75 alliance types tracked by SDC, the firms in our alliance network utilized 68. We analyzed the types that were used and limited our analysis to only include those alliance types that we expect to involve either technological or market oriented knowledge access or transfer (Grant & Baden-Fuller, 2004). In doing so, we restricted ourselves to the following 8 alliance types.

[Table 1 goes about here.]

Before analyzing our data, we removed those observations in which the firm had no alliance. We then removed those firms for which we did not have at least three years of data. and performing our statistical tests and estimates are based on the 56 firms in our sample that reported sales in at least three of the years of our sample timeframe, were in an alliance in each . We have 238 firm/year observations

Firms in the software ecosystem both cooperate and compete with each other. They are both complementors and rivals. Conventional wisdom holds that firms may cite their rivals in creating patents, but only form alliances with complementors. If this wisdom was correct, then the distinction between the networks would be due to the distinction between complementors and competitors. However, our qualitative data suggests that the distinction is not so neat. Firms form alliances with, and cite the patents of, competitors and complementors. Within the software ecosystem the term “coopetition” is used to describe this state of affairs.

Construction of Alliance network

Our approach to constructing the alliance networks follows the conventional logic (Ahuja, 2000a; Powell et al., 1996), but we include firms in the alliance network that are outside the focal firms' industry because we are interested in all the firms that contribute to the focal firm's knowledge. We define the software alliance network as a dynamic, undirected, valued graph with node and edge[7] sets N_t and E_t respectively. The firms that can enter N are one of our 71 focal firms or one of the 853 non-focal alliance partners. The average number of ties across focal firms and years is 13. A firm is in N_t if it is a participant in an alliance announcement during time [t-2, t]. We assume alliances last three (3) years because they are generally multi-year and alliance terminations are rarely reported. An edge is added to E_t connecting two nodes in N_t if the two nodes were in the same alliance during time [t-2, t]. The value of the edge is the number of alliances between the two firms in that year. The network contains alliances between focal firms, between focal and non-focal firms, and between non-focal firms.

[Table 2 goes about here.]

Table 2 is a summary of our alliance network. An interesting characteristic in our dataset is the low density of edges, low average path lengths, and high clustering of nodes. A network that is both highly locally clustered and has a short average path length is described as a 'small world' (Watts, 1999), which allows members to quickly share novel information.

Patent citation network

Patent citations have been used to measure technological significance as well to view innovation as a continuous process (Jaffe & Trajtenberg, 2002; Trajtenberg, 1990). Patent citation networks have been created to measure technological niches using patents as nodes and the citations between patents as links (Podolny et al., 1995). Prior research has also used the citations to a firm's patent portfolio as the basis for their firm-status measure (Stuart, Hoang, & Hybels, 1999) and as a measure of knowledge overlap

[7] An edge is an undirected link between two nodes.

(Mowery et al., 1996). We utilize a similar approach in creating our patent citation network where firms are nodes and the links between nodes are the citations between one firm's patent portfolio and another firm's patent portfolio. Following Podolny and Stuart's (1995) argument that patent citations represent the building of new innovations on existing ones, we argue that this represents learning by the firm that is granted the citing patent. Whereas patents may represent knowledge stock, citations represent knowledge flow.

Each patent contains information about the invention, inventor, the company to which the patent is assigned, the technological antecedents of the invention (the citations), and the technological class (of which there are over 400) to which the expert patent examiner (from the US Patent Office) has assigned the patent. Thus, the patent acts as a document-based, fossilized knowledge trace of new knowledge development. The patent applicant attempts to minimize the number of citations on the application, because citations limit the value of the new patent by reducing its scope. However, the patent examiner's job is to identify all relevant antecedents. The larger community of individuals and firms from whom the inventor is seeking protection also seeks to limit the scope of the patent by making sure that all prior art is identified. Therefore, we make the assumption that the citations represent the sources from whom the inventor learned even though these sources may be broader than those the inventor directly explored or identified.

Patent production by software companies is a recent phenomenon, and represents a small portion of the total number of software patents (Bessen et al., 2003). However, we are using patents to identify learning by software firms: we are not investigating software patents per se. The firm's motivation for patenting (which are central to other streams of research using patents, see for example: Bessen & Hunt (2003)) is not relevant here. We are using the patent citation network primarily to understand the pattern of non-contractual learning by a set of focal firms in SIC 7372 as they all confront the same appropriability regime.

We define the patent citation network as a dynamic, directed, valued graph with node and arc[8] sets N_t and A_t respectively. The firms that can enter N are one of our 71 focal firms or one of the 3,843 non-focal firms assigned a patent that one of our 71 focal firm's patent's cite. The average number of cited firms for our focal firms in any given year is 37. A firm is in N_t if it applies for a patent in time t that is subsequently granted or if it is assigned a patent that is cited in time *t* by a node in N_t. An arc is added to A_t from node B to node A in N_t if firm A applies for a patent in time t that cites a patent assigned to firm B. The value of the arc is the number of those citations. The network contains arcs between focal firms, between focal and non-focal firms, and between non-focal firms.

[Table 3 goes about here.]

An interesting characteristic of the patent-citation network in our dataset is the low density of edges, low average path lengths, and high clustering of nodes. Thus, it is similar to the alliance network in terms of the topological structure.

Operationalization of Constructs

Our dependent variable is software firm performance operationalized by firm sales. Our sample firms are all primary SIC code 7372 (prepackaged software). Sales as a proxy for firm performance have been used in some recent studies—see particularly Powell, Koput, Smith-Doerr, and Owen-Smith (2001). We measured a software firm's sales as company i's total revenues (in millions) in year t. The range for t for this study is 1995 to 1999. Because revenue values are skewed (even among the top 50 firms), we transformed the variable by taking its natural logarithm. We standardized the four network measures (reach and embeddedness in the two networks) to reduce collinearity by removing the means from each variable and dividing the subsequent values by the measure's standard deviation. As a result, all four network measures have mean 0 and standard deviation 1.

We test our hypotheses by estimating the coefficients in the following equation for each firm *i*.

[8] An arc is a directed link between two nodes.

$$Sales_t^i = V_t\alpha + W_{t-1}^i\beta + X_{t-1}^i\gamma + \varepsilon_t^i$$

The vector V_t contains industry controls (i.e., Industry size). The vector W^i_{t-1} contains focal company controls (i.e., Age, Technological similarity, and Alliance diversity). The vector X^i_{t-1} contains the network covariates (i.e., Alliance network embeddedness, Alliance network reach, Patent network embeddedness, Patent network reach).

Alliance network reach$^{\mathbf{i}}_{\mathbf{t-1}}$. We measure a company's reach by calculating its closeness centrality (Wasserman & Faust, 1994). The alliance closeness centrality of company i in year t-1 measures the capacity of the focal firm to receive knowledge from other firms in the alliance network. We make the simplifying assumption that knowledge flows in this network along optimal paths[9]. The value of each edge represents a capacity for knowledge flow. The value of a path between two firms is the minimum of the edge values (the constraining capacity) in the path connecting them divided by the number of edges (an attenuation factor) in the path. The optimal path is the path with the largest value. The closeness of a firm is the sum of the optimal paths to all other firms in the network. We lag it by one year because we anticipate sales performance to occur after the alliance is formed.

Patent network reach$^{\mathbf{i}}_{\mathbf{t}}$. We measure patent network reach through the firm's closeness centrality in the patent citation network. The patent closeness centrality of company i in year t measures the capacity of the focal firm to receive knowledge from other firms in the patent citation network and is calculated using the same logic described for alliance network reach. We assume that the knowledge borrowing that resulted in the patent application in time t occurred in time t-1; thus, the lag is built into the measure.

Alliance network embeddedness$^{\mathbf{i}}_{\mathbf{t-1}}$. Alliance embeddedness is measured by the clustering coefficient of the firm's ego network within the alliance network using undirected ties. The alliance clustering coefficient of company i in year t-1 measures the degree to which a company's alliance partners are also partners with each other (Watts, 1999). We calculate the clustering coefficient by

[9] Also the subject of a separate paper in progress.

dividing the total number of edges between company i's partners in time t-1 by the total number of possible edges between those partners (Wasserman et al., 1994).

Patent network embeddedness$^{i}_{t}$. We measure patent network embeddedness through the clustering coefficient of the firm's ego network within the patent citation network using directed ties. The patent clustering coefficient of company i in year t measures the degree to which a company's alters are also alters of each other. We calculate the clustering coefficient by dividing the total number of arcs between company i's alters in time t by the total number of possible arcs between those nodes.

Patent and alliance network reach super-additivity$^{i}_{t-1}$. We create a variable to measure super-additivity between position in the alliance network and position in the patent citation network by calculating an interaction term for our regression model. The interaction variable is the product of *Alliance network reach*$^{i}_{t-1}$ and *Patent network reach*$^{i}_{t}$.

Controls. In order to isolate the effect of network position on performance from other exogenous variables, we controlled for industry growth, firm age, firm niche, and unobserved firm heterogeneity. *Industry Size*$_t$ reflects the total revenue of all firms in SIC 7372 for year t to control for general industry growth and price changes. *Age*$_t$ is the difference between the year t and the firm's incorporation date.

We characterize market niche as the pattern of a firm's alliances – *Alliance Diversity*$_{t-1}$ – and its research interests - *Technological Similarity*$_t$. For each measure we first create a vector that represents the average for our focal firms. For *Alliance Diversity* we create vector in which each element represents an alliance type and then count the total number of alliances of each type among our focal firms. For *Technological Similarity*$_t$ we create a vector in which each element represents a patent class and then count the total number of patents assigned to each class for our focal firms. We then create firm-specific vectors following the same logic and compute the cosine of the angle between the paired vectors as in Sohn (Sohn, 2001). The cosine represents the similarity between each firm and the average among firms without regard for size differences among the firms.

We address unobserved firm-level heterogeneity in different ways in each of the four statistical estimation approaches we utilized. In our most restrictive estimation (fixed effects for firm *i*) we estimated firm-specific intercepts. In a less restrictive model (initial conditions), we utilized the initial network position of the firms at the beginning of our sample frame as a control. In our two pooled cross-sectional estimates we utilized the position of the firm in one network as a control for estimating the significance of the position of the firm in the other network. We omitted variables such as employee count, assets, or an initial period sales volume because these measures are confounded with firm performance (see Table 5).

[Table 5 about here]

Analysis

Estimation approaches

In order to test our hypotheses and the robustness of the results, we utilized four estimation approaches. These estimations included (1) a fixed effects model to control for unobserved firm heterogeneity, (2) an initial conditions model with robust standard errors, (3) a pooled ordinary least squares (OLS) regression with robust standard errors, and (4) a generalized least squares (GLS) estimator to control for panel heteroskedasticity and autocorrelation. We assumed that a single, pooled autocorrelation process applies to all panels (Beck & Katz, 1995). All statistical tests were performed with Stata®. We developed the statistical models with the intent to highlight the additive and super-additive effect of different categories of networks subject to the constraint imposed by the data available to us. Although we discuss the results of each model, we only present the details of the GLS estimates.

The fixed effects model (1) enabled us to evaluate whether we could associate small changes in network position with small changes in sales performance over a short time window while controlling for unobserved firm heterogeneity. We evaluated this model while acknowledging that the assumptions of firm independence ($Corr(X_i, X_j)=0$) and homoskedasticity of error terms across panels are violated. We used an augmented regression that nested the fixed and random effects models to determine if a random effects model was justified. We used this test, which is asymptotically equivalent to the Hausman test, instead of the Hausman test because the difference matrix the Hausman test uses was not positive definite.

The test did not indicate a random effects model was justified (P-value = 0.047). The initial conditions model (2) enabled us to evaluate whether the change in network position could explain sales performance. The OLS regression with robust standard errors (3) provided a baseline from which to examine the pooled cross-sectional relationship between network position and sales. The GLS estimation model (4) was not specified with a time-invariant control for unobserved firm heterogeneity. The GLS gives us a more consistent, robust, pooled cross-sectional evaluation of our dataset (Green, 2003) than the OLS estimation.

Results

The results of the estimates using fixed effects demonstrate that both networks are additively significant ($R2 = 0.48$, $\Delta R2 = 0.01$, $\Delta DF = 1$) and the network reach coefficients were significant and in the predicted direction (P-value < 0.05). Changes in industry size also explained changes in firm performance (P-value < 0.01). The embeddedness, diversity, and opportunity variables were dropped from the model because they were not significant either in a model consisting only of controls or in the full model. Including them in the full model only served to confound the results we did see. The super-additivity coefficient was not significant.

The results of the estimates using initial conditions demonstrate that both networks are additively significant ($R2 = 0.47$, $\Delta R2 = 0.01$, $\Delta DF = 1$) and the network reach coefficients were significant and in the predicted direction (P-value < 0.05). Firm age was also positively associated with firm performance (P-value < 0.01). As in the fixed effects model, the embeddedness, diversity, and opportunity variables were dropped from the model because they were not significant either in a model consisting only of controls or in the full model. Including them in the full model only served to confound the results we did see. The super-additivity coefficient was not significant.

The results of the estimates using OLS regression with the Huber/White/sandwich estimator of variance demonstrate that both networks are independently and additively significant ($R2 = 0.43$, $\Delta R2 = 0.06$, $\Delta DF = 3$). The reach measures are both significant and in the predicted direction (P-value < 0.05).

The alliance emebeddedness measure is also significant and in the predicted direction (P-value < 0.05). The Patent network embeddedness, Alliance diversity, and technological opportunity variables were included in the model, but they were not significant. The super-additivity coefficient was not significant.

We show the results of the GLS estimators in Table 6. The continuous improvement in model fitness as variables are added provides support for the general hypothesis that the networks have individual, additive, and super-additive explanatory power. Controlling for the firm's position in the alliance network, its position in the patent citation network adds to the explanatory power. Similarly, controlling for the firm's position in the patent citation network, adding the firm's position in the alliance network adds explanatory power. Finally, the addition of an interaction variable, testing for super-additivity, improves the model. The hypotheses tests and general observations regarding the regression coefficients are performed with the full, final model with autocorrelation correction (column 6).

We use the coefficient of alliance network reach to test H1. The coefficient is 0.20 ($p < 0.01$) and supports H1. The corresponding coefficient for patent network reach is also positive (coefficient: 0.23, $p < 0.01$) supporting H3. Both types of network reach have positive effects.

For the alliance embeddedness hypothesis (H2), we had two competing expectations that differ in terms of the directionality. The coefficient for alliance embeddedness has a negative effect on performance (coefficient: -0.06, $p < 0.05$). Thus, the arguments for the negative effect of embeddedness are supported. The coefficient of patent network embeddedness coefficient tests hypothesis H4. The results are inconclusive since the coefficient is not significant.

We test our additivity hypothesis (H5) by looking at the change in model fitness when going from one network to two. A firm's joint position in the contractual and non-contractual networks is more closely correlated with firm performance than either network alone ($p < 0.001$). The coefficient of the network reach interaction term tests hypothesis H6. We find that a firm's reach in the contractual and non-contractual networks is super-additively associated with performance (coefficient: 0.07, $p < 0.05$).

[Table 6 goes about here]

Collinearity and endogeneity tests

One of our concerns in our statistical modeling is testing for, and properly treating, collinearity -- both networks are actually measuring the same thing -- and endogeneity -- a firm's position in one network (e.g., the alliance network) leads to its position in the other (e.g., the patent citation network). The latter concern is particularly significant because of the number of alliance studies that use patents as an outcome measure of alliances (Ahuja, 2000a; Mowery et al., 1996; Mowery, Oxley, & Silverman, 1998). The more general endogeneity hypothesis is that a missing variable or set of firm characteristics that is more directly under the control of the firm predicts network position, and that network position is a proxy for this missing measure.

The collinearity concern can be addressed by examining the correlation between the two reach measures (see Table 5). The moderate correlation suggests that network positions in the different networks are relatively independent. We also tested variable inflation factors after regression to confirm the absence of undue collinearity. The endogeneity concern among the constructs in our study is that firms forming an alliance cite each others' patents (Mowery et al., 1996, 1998). If this relationship were strong, a firm's alliance partners would predict the firms whose patents it cites and its subsequent position in the alliance network would predict its position in the patent citation network. The visualization in Appendix A suggests that the relationship between patent citation and alliance formation is not strong. We also used an instrumented variable regression model to confirm that the neither network is more endogenous than the other. When the instrumented variable was patent network reach and the instruments were alliance network reach and age, exogeneity was not rejected (P-value = 0.45). When the instrumented variable was alliance network reach and the instruments were patent network reach and age, exogeneity was not rejected (P-value = 0.27). The more general concern regarding a missing variable is endemic to all firm-level studies. We address this using the fixed effects estimator[10]. We also rely on extant theory that suggests both alliance formation and spillover capture are subject to managerial discretion (Cohen et al., 1990; Gulati et al., 1998). We recognized the possibility that different firms have different philosophies regarding patenting and alliance formation. We controlled for these strategic choices when selecting our sample frame.

We build our model additively in five stages to examine the specific performance effects of a firm's set of network characteristics. In model 1 we consider industry and firm controls. In model 2 we add variables that represent the firm's position in the alliance network. In model 3 we replace the alliance network measures with patent citation network measures in order to consider the importance of each network independently. In model 4 we combine the network measures from both the alliance and patent citation networks in order to consider their additive qualities. In model 5 we test for an interaction effect between the alliance and patent citation networks.

Network Visualization

Why network visualization. Network visualization creates a capacity for building intuition and theorizing about a phenomena that is unsurpassed by statistical analysis (Moody, McFarland, & Bender-deMoll, 2005). Wide-ranging distributional shapes, nonlinear relations, and spatial proximity are particularly well suited to visual summarization. We utilize network visualization to both help identify the phenomena — firms existing in dual networks — and changes to the topology of the networks themselves (Powell et al., 2005). Through the use of visualization we have a much richer, intuitive understanding of the distinctness of the dual networks and the firm's joint position within them. Such visualizations complement our statistical inferences, which we use for hypothesis testing.

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[10] We tested endogeneity in the fixed effects model using the same logic as in the regular regression model. The results were similar (P-value = 0.34 when rejecting exogeneity of alliance network reach and P-value = 0.11 when rejecting exogeneity of patent network reach).

How we depict the network. Appendix A contains a series of Pajek (de Nooy, Mrvar, & Batagelj, 2005) visualizations. The images show the networks we constructed for 1995 and 1999[11]. For each year, we show the entire network and the ego networks (the network consisting of a focal firm and its adjacent alters) for Microsoft Corporation and Adobe Systems Incorporated. We selected Microsoft because it is the largest firm within our focal set and we selected Adobe as a typical modal firm with a moderate number of patents and alliances. For each network, we show three views: the alliance network, the patent citation network, and the joint alliance and patent citation network. The focal firms are highlighted in red boxes, sized proportional to the logarithm of their sales. The edges (lines) between nodes are colored according to relationship type. Alliance relationships are shown in blue, patent citation relationships are shown in green, and relationships involving both alliances and patent citations are shown in red.

What the visualizations tell us. Two striking observations become apparent after examining figures 2 and 3. The very low number of red lines implies that a firm's alliance partners are not the ones that it cites in its patents. This provides additional corroboration for the additivity hypothesis that was empirically confirmed through statistical analysis. However, the visualization provides an additional insight that goes beyond the statistical analysis: the focal firms are not the most *central* in their own networks. This is somewhat surprising since we specifically included only those firms that had an alliance or patent citation relationship with the focal firms when we created the networks.

As shown in figures 2 and 3, the focal firms are in the periphery of their alliance network both in 1995 and 1999. The patent citation network visualizations indicate similar profiles. The packaged software companies are learning from many other firms, which are also learning from each other. Although the visualizations suggest the networks are quite dense, the statistics (network density across networks and years varies from 0.4% to 0.8%) suggest that the networks are actually quite sparse. The core-periphery structure we observe in the visualizations is consistent with high small-world measures

[11] Yearly rendering is not done due to space limitations. A full set of "movies" that show the full network and company-specific ego networks for Microsoft Corporation and Adobe Systems Incorporated for each year in the sample frame are available from the authors.

(the ratio of the network's cluster coefficient to average path length compared to a random network's with the same number of nodes and density varies across network and years from 45.5 to 114.7) (Watts, 1999).

The small-worldiness enables information to travel quickly between otherwise unconnected nodes. Whether the value of high-reach predicts performance because of more distinct information or because high-reach increases the probability of receiving valuable information, requires further investigation. What we can say is that the firms with high reach seem to be better positioned to receive valuable information.

Going beyond the overall network to the visualizations of Adobe's and Microsoft's networks, we find similar patterns. First, in both cases we see that some of the firms' partners are redundant – the partners are linked to each other – and some are distinct. Second, there are very few linkages that show *both* alliance and patent citation relationships — implying that these firms are accessing distinct networks to gain access to distinct, valuable information. Thus, the visualizations, while serving to corroborate the statistical tests, also provide useful insights to further examine patterns of interconnected networks across domains.

We do not have a clear understanding as to why there is so little overlap between the two networks. Prior research suggests that firms in an alliance are more likely to cite each other's patents than those that are not (Mowery et al., 1996, 1998). Clearly, a statistically significant increase in likelihood does not preclude citations without being in an alliance nor does it require that the majority of firms a firm cites be an alliance partner. The increased likelihood of citing an alliance partner would also rule out the hypothesis that firms form alliances in lieu of patenting. Firms patent to protect their intellectual property from firms other than their alliance partners. Perhaps the best explanation of this phenomenon is the strong form of the transaction-cost argument we put forward earlier: to the extent the networks confer the same value, only the one that does so at the lowest cost will persist. That both networks exist suggests that the networks are independent. Firms develop conduits to multiple other firms in order to access unique, additive, and super-additive resources.

The lack of overlap is also consistent with our qualitative data. The firms we spoke with maintain different relationship management functions for different types of relationships. Some relationships are considered strategic alliances. These relationships are formed around the sales function and are anticipated to drive revenue. These relationships may incorporate some technological functions, but they tend to be sales and customer driven. Other relationships are formed in order to support the development of products. These relationships are used to explore new technologies that may be subsequently incorporated into a product line. There are clearly separate relationships that result in separate networks with separate functions that ultimately drive revenue. There is also overlap between the functions and some movement of a firm between networks (a technology partner becomes a strategic alliance) to give rise to super-additive performance boost.

Discussions

Most studies on organizational networks focus on single networks — more specifically: alliances and partnerships formed by a set of firms within an industry or set of industries. In this research we have extended the conceptualization of a firm embedded in a single network to one in which a firm is embedded in multiple, possibly overlapping, networks to access complementary knowledge resources that underlie success in software industry networks. We developed a simple, parsimonious typology of networks. Firms enter into the relationship with other firms that are either fine-grained, formal, and contractual, or coarse-grained, non-formal, and non-contractual. We modeled the set of relationships as a network and theorized, and empirically observed, that software firms embed themselves in these dual networks governed by different mechanisms. We theorized that firms enter into these networks in order to gain access to knowledge resources, that these resources differ in different networks, and that firms maneuver within specific networks to access specific knowledge at the lowest cost. As a result, the networks specialize in the knowledge that flows within them. The networks (the underlying relationships and accessed knowledge) are both independently beneficial to the firm and complementary to each other. Our main empirical contribution is that within the set of leading software firms that we studied, firms' positions within these networks are both additive and super-additive in terms of firm performance measured by sales.

Networks of relationships are important resources as they allow firms to access different types of knowledge — they may involve market intelligence, product information, and technical knowledge. Some types of knowledge may be product oriented (impacting the design and deployment of new software products) while others could be process focused (to coordinate the delivery of interdependent software products). Some types of knowledge are codified while others are more tacit. Such complexities require firms to construct the best set of mechanisms to access these different types of knowledge. We hypothesized that the knowledge accessed by a firm's position in the different networks is distinct and complementary and that the value of each type of knowledge is increased as the firm has more of the other type. The firm's position in each network is also complementary to the firm's efforts to improve its position in the other network. An enhanced position in the contractual network improves the firm's ability to position itself in the non-contractual, and vice versa. Our preliminary results in one setting raise the need for further theorizing about how different types of resources can be accessed through different types of mechanisms, and further examination of whether they are additive and super-additive or not. This will go towards developing a richer and more micro-level understanding of networks as critical resources (Gulati et al., 1999) under different conditions.

This research overcomes two limitations in prior research on network formation and value appropriation. First, most studies focus on a single type of business relationship – technology alliances, marketing relationships, vendor relationships, or joint R&D activities – or different types of non-contractual relationships – employee mobility, interlocking directorates, or social ties. This research creates an initial typology in which business relationships can be characterized as contractual or non-contractual. Each type has a distinctive governance mechanism and knowledge type. This study suggests that, for example, alliance relationships are an instance of a more general classification – contractual relationships – that may share many affordances and be subject to many of the same challenges.

Second, because most studies lacked a clear distinction between network types, they did not explore the ramifications of the multiple networks in which firms are embedded. In characterizing a firm as belonging to two classes of networks, we are able to explore their additive and complementary qualities. We anticipate that as the typology of relationship types is expanded, the additional categories will share the qualities of being additive and complementary. Promising candidate frames include interlocked boards of directors[12], participation in open source projects, and inter-firm equity linkages.

This study makes three methodological contributions. First, we measure a firm's position in its non-contractual network through the creation of a patent citation network. We showed through Pajek visualizations and summary statistics that knowledge flows across multiple networks and provided a method for documenting non-contractual approaches to knowledge access. Second, we measure and test dual network position by collecting data on two networks. Specifically, we followed a consistent protocol to create these two networks and then used them in a single statistical model. Future refinements may explore methods of assessing how firms position in multiple networks more holistically. Third, we combine statistics with visualizations to understand dual networks, as they appear to provide complementary insights. Future refinements may enhance more systematic ways to create interplays between statistics and visualizations as ways to both develop and test theoretical assertions.

Our findings also have important implications to practice — especially for designers of organization structure, processes and systems. How should a firm coordinate the different knowledge conduits embedded within different knowledge networks? Does the firm require new structural roles, new processes for alliance formation, and new mechanisms for managing non-contractual relationships? How can knowledge management systems be designed to reflect the multi-faceted nature of knowledge and its absorption (Kale, Dyer, & Singh, 2001)? Some researchers have called for specific structural roles for coordinating the value from alliances (Kale, Singh, & Perlmutter, 2000). Our findings raise the need for

[12] We performed preliminary tests which suggests that network position in the directorate interlock network is additive in our regression model. However, we have insufficient data to construct a network of all the interlocks

new structural roles, different process for absorbing different types of knowledge, as well as systems that allow for combining multiple types of knowledge for maximal performance. Each network in which a firm is positioned has its own governance mechanism and offers access to unique and possibly complementary set of resources. The time is ripe for the systematic consideration of organizational architecture that goes beyond a single firm's boundaries and incorporates an extended set of alliances and partnerships that may be governed through multiple types of mechanisms.

Limitations and Extensions

We enumerate a set of limitations underlying this study as avenues of future extensions. First, our research limited to the top firms in the prepackaged software industry (SIC 7372) should be replicated and extended to establish the robustness of findings—especially the additive and super-additive properties. Second, our study relied primarily on secondary data. The research design should benefit greatly from primary assessments of how information and knowledge is absorbed from multiple networks. What information flows from the different networks? What information from which networks is most valuable to the firm? How do firms actively leverage their position in one network in the other? How do firms combine the different types of knowledge? Third, one of the limits in any network study is the definition of the network. At some level, all firms are connected to all other firms. However, the attenuation of information across links being what it is, and the impracticality of identifying all links, requires that we define the network narrowly. Broadening the scope of knowledge access may enhance the confidence in the findings. Similarly, our results based on the software industry—with implicit need for inter-firm cooperation for complementary knowledge—are worthy of tests in other industries that may rely less on inter-firm knowledge flows to develop more insights on the contingency nature of dual or multi networks.

As in many other industries, software firms form alliances in order to develop knowledge, gain access to valuable resources, and signal their status to other firms. The resources that the firms we spoke with

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using the node selection methods we chose for the alliance and knowledge-spilling networks. Our preliminary directorate-interlock tests were based upon a network consisting only of our focal 71 firms.

deploy to manage their partnerships, and the statements they made to us as to what they expect from them, suggests the importance of the knowledge acquisition perspective and support the general causal direction employed in our statistical models and theories. However, we cannot rule out the possibility that the conditions that lead to firm performance also lead to improved network position. That is, network position reflects performance and doesn't lead to it. Future research should look into the relationship between alliance partners as a signal for unobservable value (Spence, 1973; Stiglitz, 2000) and alliances as a conduit for knowledge.

Patents are similarly multi-dimensional. Patents represent innovation and also serve as a barrier to competition. Thus, patent citations – one of the subjects of this study – may represent knowledge flow as well as the jockeying for position among firms. Are learning and jockeying independent, additive, or substitutes?

The networks in our study were all scale-free small-worlds in which the number of edges touching a specific node follows a power-law distribution. That is, the networks are characterized by a few nodes having a great many links, and many nodes having very few links. In order to generalize our findings, future research should explore the results of this research in network topologies with different characteristics. For example, these results may not hold if the network is not a small-world or is not also scale-free.

In constructing our networks we aggregated different mechanisms for knowledge exchange. In the alliance network we combined eight different types of alliances with the argument that they were all fine-grained and, therefore, qualitatively more similar to each other than to the exchange mechanisms that characterize the coarse-grained, non-contractual network. Similarly, we argued that the various coarse-grained mechanisms for spillover capture captured information that was more similar to each other than to the information exchanged in any of the different types of alliances. However, the logic employed in this paper should be extendable to the individual networks we conceptualized. Each type of alliance could be treated differently and could define its own, related network. Each mechanism of spillover capture could similarly capture different types of information and be considered in a separate, related network.

The longitudinal estimates derived from the fixed effects, initial conditions, and GLS models allow us to make a stronger causal claim on network position causing sales performance than the pooled OLS model. However, each model is not without its limitations. The first two models are not as robust as we would expect. We would have liked to include more variables and see a larger change in explained variance. The GLS model does not control for firm heterogeneity as robustly as we would like. All the models would benefit from additional firms and additional years of data.

Network-based research has added to our understanding of the firm as both consisting of internal networks (i.e., formal, informal, advice, friendship, etc.) and existing within a networked ecosystem. No doubt, the internal networks influence the firm’s behavior in the external ecosystem. However, the networked ecosystem is, itself, a network of networks. From a network analysis perspective, firms exist simultaneously in multiple networks, and these networks are interdependent. Analyzing a firm in one network without taking into account the interrelated others leaves much of the story untold. The networks may overlap to varying degrees, provide complementary resources, or jointly constrain the firm. This paper has made the first step towards examining a firm’s role in creating and exploiting these interlocked networks, but much work remains.

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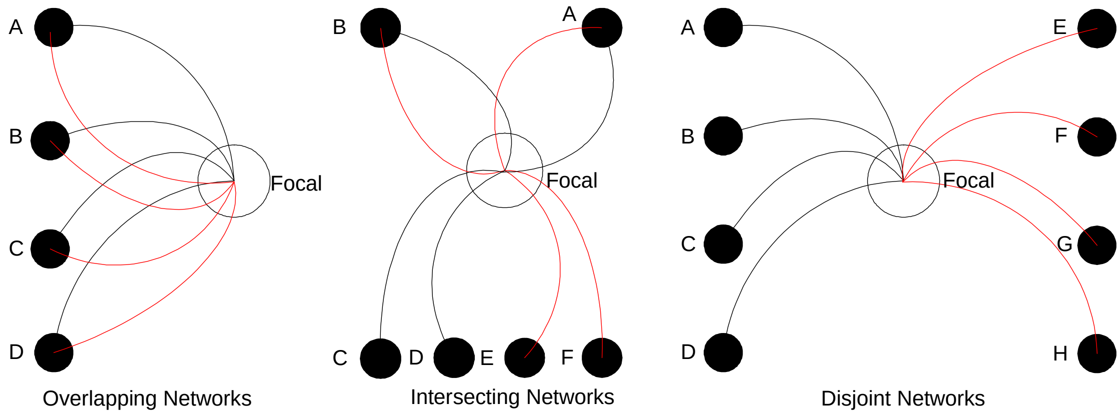

Figure 1: Three Stylized Positions for a Focal Firm in Two Networks.

Table 1: Alliance classification codes.

Code	Activity Description
ELS	Exclusive Licensing Services
CPS	Computer Programming Services
CST	Consulting Services
SDS	Software Development Services
CIS	Computer Integrated Systems Services
MRK	Marketing Services
RDS	Research & Development Services
LIC	Licensing Services

Table 2: Alliance network characteristics

Year	Node Count	Edge Count	Density[13]	Average Path Length[14]	Cluster Coefficient[15]
1995	778	2,548	0.008	3.393	0.390
1996	777	2,279	0.008	3.428	0.369
1997	790	2,071	0.007	3.480	0.364
1998	769	1,934	0.007	3.479	0.346
1999	835	1,850	0.005	3.548	0.363

[13] Density is the ratio of actual ties between firms to the potential number of ties between firms. In an undirected network Density = 2*E/(N*(N-1)) where E is the number of edges and N is the number of nodes. In a directed network Density = E/(N*(N-1)).

[14] The average path length is computed by calculating the geodesic (path with fewest edges) for each pair of nodes and then calculating the average of those geodesics.

[15] The cluster coefficient for a graph is calculated by first calculating the density of each node's ego network and then calculating the average of those values. An ego network for a node is the network that consists of the focal node plus the nodes that are directly connected to it.

Table 3: Patent citation network characteristics.[16]

Year	Node Count	Arc Count	Density	Average Path Length*	Cluster Coefficient
1995	2,986	62,548	0.007	2.51	0.427
1996	3,235	66,922	0.006	2.51	0.436
1997	3,459	74,213	0.006	2.47	0.456
1998	3,438	67,838	0.006	2.49	0.468
1999	3,206	53,571	0.005	2.57	0.453

*Reachable pairs only.

[16] See notes for Table 2 for a description of how these measures were calculated.

Table 4: Descriptives for years 1995-1999

	Mean	Standard Deviation	Skewness	Kurtosis	Min	Max
Sales	943.99	2159.69	5.35	36.83	7.72	19747.00
Industry size	117.57	22.81	0.08	1.72	85.57	150.73
Age	14.74	8.36	0.82	3.58	0.00	43.00
Alliance net. reach	236.42	83.93	-0.04	5.78	1.00	518.00
Alliance net. embed	0.09	0.15	2.75	12.08	0.00	0.86
Alliance diversity	0.80	0.15	-0.83	3.15	0.34	1.00
Patent net. reach	2589.29	3323.48	1.77	6.52	0.00	16826.00
Patent net. embed	0.19	0.20	0.79	2.66	0.00	0.75
Technological similarity	0.27	0.30	0.63	1.94	0.00	0.98

238 observations for each variable.

Table 5: Pooled correlations for years 1995-1999

	1	**2**	**3**	**4**	**5**	**6**	**7**
1. Sales (log)	1.00						
2. Employee count (log)	0.94**	1.00					
3. Alliance network reach	0.41**	0.40**	1.00				
4. Alliance network embeddedness	-0.14*	-0.04	0.17**	1.00			
5. Alliance opportunity	0.33**	0.38**	0.44**	-0.05	1.00		
6. Patent network reach	0.55**	0.52**	0.53**	-0.02	0.30**	1.00	
7. Patent network embeddedness	0.05	0.12	0.03	-0.04	0.07	0.31**	1.00
8. Technological similarity	0.40	0.39**	0.38**	-0.03	0.18**	0.79**	0.49**

* indicates significance $p < 0.05$. ** indicates significance $p < 0.01$.

Table 6: Firm Performance and Network Position

	GLS Pooled Cross-Sectional Estimates. Observations are firm, year (i, t). Dependent Variable = Sales$_t$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Controls	Alliance Position	Patent Position	Alliance and Patent Position	Super-additivity	Auto-correlation
Industry size$_t$	0.09	0.15	0.13	0.14	0.14	0.13
	(6.0)**	(14.0)**	(9.1)**	(9.7)**	(9.9)**	(9.6)**
Age$_t$	0.03	0.03	0.04	0.03	0.03	0.03
	(8.2)**	(6.9)**	(10.9)**	(8.3)**	(8.5)**	(5.7)**
Alliance diversity$_{t-1}$		0.31		0.25	0.24	0.15
		(9.8)**		(6.5)**	(6.2)*	(4.1)**
(H1) Alliance net reach$_{t-1}$		0.39		0.11	0.11	0.20
		(9.7)**		(2.9)**	(3.0)**	(5.0)**
(H2) Alliance net embed. $_{t-1}$		-0.23		-0.13	-0.12	-0.06
		(9.4)**		(3.7)**	(3.4)**	(2.2)*
Technological similarity$_t$			0.03	0.04	0.06	-0.02
			(0.43)	(0.72)	(0.98)	(0.48)
(H3) Patent net reach$_t$			0.62	0.48	0.40	0.23
			(10.2)**	(7.8)**	(5.7)**	(3.9)**
(H4) Patent net embed.$_t$			-0.05	-0.03	0.01	0.02
			(1.1)	(0.63)	(0.31)	(0.60)
(H6) Reach super-add $_{t-1}$					0.06	0.07
					(2.2)*	(2.1)*
Constant	4.5	4.0	3.8	3.8	3.8	3.9
	(23.2)**	(29.7)**	(20.7)**	(20.7)**	(20.4)**	(21.9)**
Observations	238	238	238	238	238	238
Number of panels	56	56	56	56	56	56
Chi-Squared	100.53	649.82	442.51	512.96	536.31	242.33
Log Likelihood	-266.86	-232.06	-238.85	-225.17	-222.73	-142.49
Degrees Of Freedom (DF)	2	5	5	8	9	9
Model fitness (-2LL)	533.72	464.12	477.70	450.34	445.46	
Model comparison logic		**(2) – (1)**	**(3) – (1)**	**(4) – (2)**	**(5) – (4)**	
Δ(-2LL)		69.60	56.02	13.78	4.88	
Δ(DF)		3	3	3	1	
P-Value Chi2 diff. (Δ(-2LL), Δ(DF))		0.000	0.000	0.003	0.027	

Absolute value of z statistics in parentheses. * indicates significance $p < 0.05$. ** indicates significance $p < 0.01$.

Appendix A – Visualizations

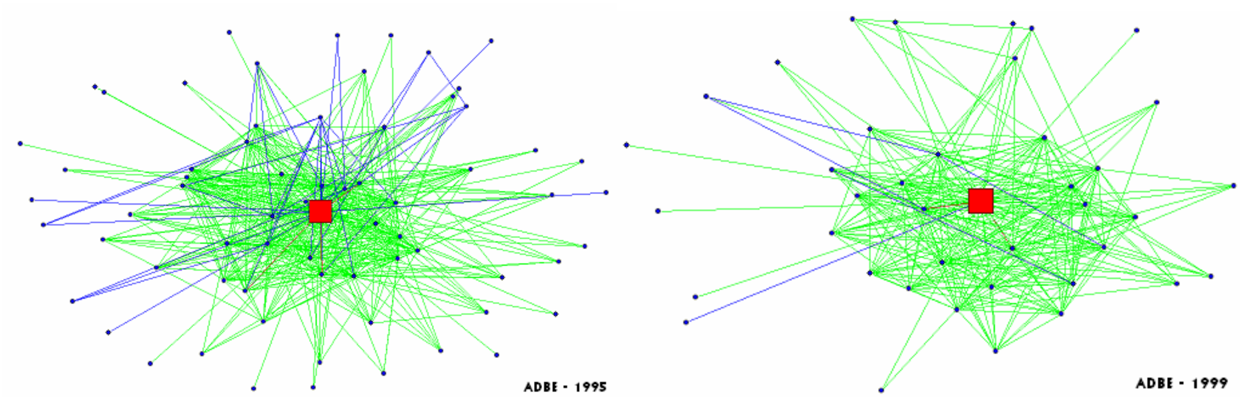

Figure 2. Adobe's ego network drawn from dual networks – 1995 and 1999. Adobe is the red square, its alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.

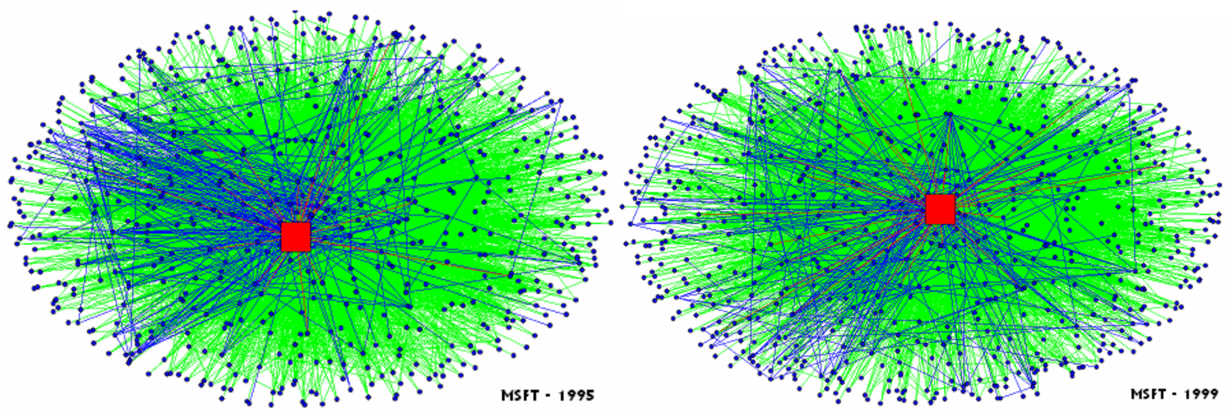

Figure 3. Microsoft's ego network drawn from dual networks – 1995 and 1999. Microsoft is the red square, its alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.

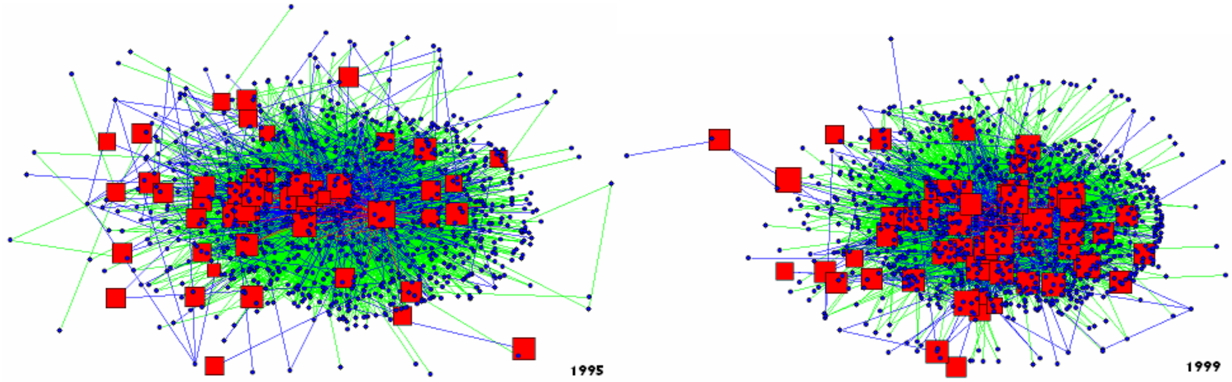

Figure 4. Software industry dual networks – 1995 and 1999. The top 71 firms in SIC 7372 are the red squares (sized by the logarithm of reported sales), their alters are the blue circles, green lines represent ties exclusive to the patent-citation network, blue ties represent ties exclusive to the alliance network, and red ties represent overlapping ties in the dual networks. Visualization done in Pajek.